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# Optimization Models for Biorefinery Supply Chain Network Design under Uncertainty

Narges Kazemzadeh  
*Iowa State University*

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**Optimization models for biorefinery supply chain network design  
under uncertainty**

by

Narges Kazemzadeh

A thesis submitted to the graduate faculty  
in partial fulfillment of the requirements for the degree of  
MASTER OF SCIENCE

Major: Industrial Engineering

Program of Study Committee:

Guiping Hu, Major Professor

Sarah Ryan

Frank Montabon

Iowa State University

Ames, Iowa

2013

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## ABSTRACT

Biofuels are attracting increasing attention worldwide due to its environmental and economic benefits. The high levels of uncertainty in feedstock yield, market prices, production costs, and many other parameters are among the major challenges in this industry. This challenge has created an ongoing interest on studies considering different aspects of uncertainty in investment decisions of the biofuel industry.

The Renewable Fuel Standard (RFS) sets policies and mandates to support the production and consumption of biofuels. However, the uncertainty associated with these policies and regulations of biofuel production and consumption have significant impacts on the biofuel supply chain network.

The goal of this research is first to determine the optimal design of supply chain for biofuel refineries in order to maximize the annual profit considering uncertainties in fuel market price, feedstock yield and logistic costs. In order to deal with the stochastic nature of the parameters in the biofuel supply chain, we develop two-stage stochastic programming models in which Conditional Value at Risk (CVaR) is utilized as a risk measure to control the amount of shortage in demand zones. Two different approaches including the expected value and CVaR of the profit are considered as the objective function.

This study also aims to investigate the impacts of the governmental policies and mandates on the total profit in the biofuel supply chain design problem. To achieve this goal, the two-stage stochastic programming models are developed in which conditional value at risk is considered as a risk measure to control the shortage of mandate.

We apply these models for a case study of the biomass supply chain net-



work in the state of Iowa to demonstrate the applicability and efficiency of the presented models, and assess the results.

## CHAPTER 1. GENERAL INTRODUCTION

### 1.1 Introduction

There is a growing interest in the use of biomass as an important source of energy in the world. Biomass currently accounts for roughly 10% of the total primary energy consumption [15]. Biofuel is referred to as fuels for the transport sector produced from biomass which can be used as a substitute for petroleum fuels. [11]. The reasons to promote the biofuel production include energy security reasons, environmental concerns, foreign exchange savings, and socioeconomic benefits for the rural development [12].

There are several advantages for developing biofuels: biofuels have potential to reduce dependency on fossil fuel; they are easily available from common biomass sources; biofuels have a considerable environmentally friendly potential; they promote rural development in agricultural regions; they are biodegradable and contribute to sustainability. In summary, biofuel production provides many benefits the environment, economy and consumers [15, 33, 11].

One of the most important aspects of biofuel production planning is the design of biomass supply chain networks. However, the biofuel industry has been challenged by the significant uncertainties along the biofuel supply chain such as the available feedstock supply, logistic costs and consumer demands. Therefore, it is of great importance to consider the impacts of uncertainties to the biofuel supply chain network design.

The government regulations and policies affect the production and use of biofuel across the biofuel supply chain. These policies are necessary to success-

fully deploy biofuel production since the production of biofuels is often more expensive than the production of conventional fuels [15, 33]. Biofuel industry is highly affected by the policies and regulations. In this study, the impacts of policies on the biofuel supply chain network design are investigated.

The proposed mathematical modeling framework aims to design a biorefinery supply chain considering uncertainties in fuel market price, feedstock supply, and logistic costs including transportation and operation costs. Mixed integer programming models with a two-stage stochastic programming approach were applied to address the uncertainties. The first-stage makes the capital investment decisions including the locations and capacities of the biorefineries. Once the first-stage decisions are determined, the second-stage determines the biomass and gasoline flows. The objective function is to maximize the annual profit. Two different types of objectives were considered: expected value of profit,  $E(Profit)$ , and conditional value at risk of profit,  $CVaR(Profit)$ . The proposed models also illustrate the impacts of incorporating CVaR in constraints on satisfying biofuel demand or mandate and controlling the amount of shortage in demand zones. The impacts of the changes in policies and mandates on the proposed models are discussed.

## 1.2 Thesis Structure

Chapters 2 and 3 correspond to the research goals outlined above. In chapter 2, we develop the mathematical models with the approach of two-stage stochastic programming to design a biorefinery supply chain considering uncertainties in the fuel market price, feedstock supply, and logistic costs. Chapter 3 is devoted to the evaluation of the impacts of biofuel policies such as mandate and pass-through on the biofuel supply chain design. Finally, Chapter 4 summarizes the conclusions drawn from the thesis and plans for future work in this area.

## CHAPTER 2. OPTIMIZATION MODELS FOR BIOREFINERY SUPPLY CHAIN NETWORK DESIGN UNDER UNCERTAINTY

Narges Kazemzadeh<sup>1</sup> and Guiping Hu<sup>2</sup>

Department of Industrial and Manufacturing Systems Engineering, Iowa State  
University, Ames, IA 50011, USA

### Abstract

Biofuel industry has attracted much attention due to its potential to reduce dependency on fossil fuels and contribute to the renewable energy. The high levels of uncertainty in feedstock yield, market prices, production costs, and many other parameters are among the major challenges in this industry. This challenge has created an ongoing interest on studies considering different aspects of uncertainty in investment decisions of the biofuel industry.

This study aims to determine the optimal design of supply chain for biofuel refineries in order to maximize annual profit considering uncertainties in fuel market price, feedstock yield and logistic costs. In order to deal with the stochastic nature of parameters in the biofuel supply chain, we develop two-stage stochastic programming models in which Conditional Value at Risk (CVaR) is utilized as a risk measure to control the amount of shortage in demand zones. Two different approaches including the expected value and CVaR

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<sup>1</sup>kazemzad@iastate.edu

<sup>2</sup>gphu@iastate.edu

of the profit are considered as the objective function. We apply these models and compare the results for a case study of the biomass supply chain network in the state of Iowa to demonstrate the applicability and efficiency of the presented models.

### **keywords**

supply chain management, biorefinery , stochastic programming , biofuel , CVaR

## **2.1 Introduction**

Biofuel, as an important source of energy, has created increasing interest in the past few years due to its environmental and economic benefits. One of the most significant advantages of biofuel is its potential to reduce dependency on fossil fuel. Moreover, second generation biofuel provides the benefit of avoiding competition with food production and promotes rural development in agricultural regions by using lignocellulosic biomass as feedstock [15].

U.S. Environmental Protection Agency (EPA) regulations affect the production and use of biofuel across the biofuel supply chain. EPA has proposed rules in a revised Renewable Fuel Standard (RFS-2) that govern how biofuels are produced and used in the U.S. RFS-2 has set a goal of producing 36 billion gallons of biofuels in 2022 as shown in Figure [2.1](#).

One of the most important aspects of biofuel production planning is the design of biomass supply chain networks. Thus far, numerous studies have been conducted on supply chain design of biorefineries [16, 42, 28]. However, the biofuel industry has been challenged by the significant uncertainties along the biofuel supply chain such as the available feedstock supply, logistic costs and consumer demands. Therefore, it is of great importance to consider the impacts of uncertainties to the biofuel supply chain network design.

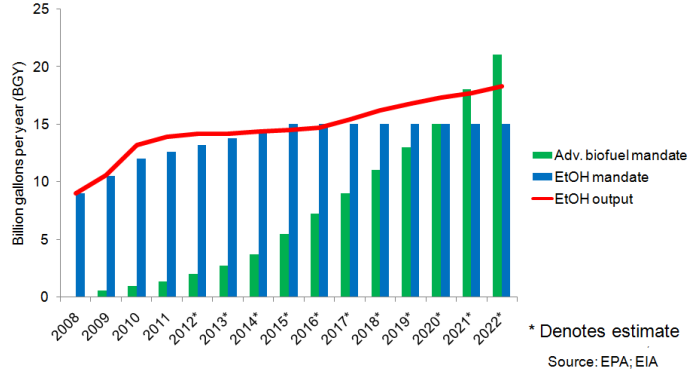


Figure 2.1 Renewable Fuel Standards (RFS-2) goal (Source: EPA, EIA)

There is a rich literature on supply chain design. An et al. [3] reviewed previous research on biofuel and petroleum-based fuel supply chain. Shah [38] discussed the advantages and challenges of the process industry supply chain optimization. The author reviewed the studies in infrastructure design, modeling, analysis, planning, and scheduling together with some industrial examples. Bowling et al. [7] present an optimization model with the objective of maximizing net profit considering overall sales and the costs for the feedstock, transportation costs, capital costs for the facilities, and the operational costs for the facilities. The objective was to maximize net profit considering overall sales and the costs for the feedstock, transportation costs, capital costs for the facilities, and the operational costs for the facilities. Eksioglu et al. [16] proposed a mathematical model to design the supply chain of biorefineries needed to produce biofuel. The model determines the number, sizes and locations of the biorefineries. The authors applied the model for the state of Mississippi in a case study. Gan [17] developed an analytical framework for supply of biomass considering feedstock production, energy conversion, and environmental benefits/costs to minimize the total cost of both feedstock and electricity production and determine the optimal power plant size. In [41], the authors used GIS to determine the optimal locations, sizes and number of bio-energy facilities in Alberta, Canada while optimizing the transportation cost. An in-

tegrated mathematical model to determine the optimal comprehensive supply chain/logistics decisions to minimize the total cost is proposed by Zhang et al. [46] They showed the application of this model with a case study in the state of North Dakota. Vera et al. [43] developed a framework for finding the optimum location and capacity of a power plant fed with residues from olive oil producing areas.

An optimization model for the strategic design of a hybrid first/second generation ethanol supply chain is developed by Akgul et al. [1]. This model addresses sustainability issues such as the use of food crops, land use requirements of second generation crops, and competition for biomass with other sectors. They considered bioethanol production in the UK using hybrid first/second generation technologies as the case study. In another work, they proposed a multi-objective optimization model of hybrid first/second generation biofuel supply chains to analyze the trade-off between the economic and environmental objectives as well as the impact of carbon tax on the economic and environmental performance of the biofuel supply chain. The authors demonstrated the applicability of the model with a case study of bioethanol production in the UK [2]. Kim et al. [27] developed a mixed integer linear programming model to determine the fuel conversion technologies, capacities, biomass locations, and the logistics of transportation from the locations of forestry resources to the conversion sites and then to the markets. The authors used the model to analyze the supply chain systems and particularly to verify which parameters have major impacts on the overall economic outlook. The benefit of converting to a more distributed type of processing network has been analyzed, in terms of the overall economics and the robustness to demand variations. Judd et al. consider the impact of biomass crop yield, harvest method, and economies of scale in biorefinery capacities on the total cost [23]. The problem of finding the best location for a biorefinery plant considering the local availability of biomass and

geographical distribution of customers has been studied by Leduc et al. [29].

A number of studies considered dynamic models planning over multiple periods. Huang et al. [22] proposed a mathematical model that integrates spatial and temporal dimensions for strategic planning of future bioethanol supply chain systems. The planning objective was to minimize the cost of the entire supply chain of biofuel from biowaste feedstock fields to end-users over the entire planning horizon, simultaneously satisfying demand, resource, and technology constraints. As a case study, the authors applied the model to investigate the economic potential and infrastructure requirements for bioethanol production from eight waste biomass resources in California. Sokhansanj et al. [40] developed a dynamic integrated biomass supply analysis and logistics model to simulate the collection, storage, and transport operations of supplying agricultural biomass to a biorefinery. A dynamic nonlinear mixed integer programming model is developed by Shabani and Sowlati [37] to maximize the overall value of the supply chain of forest biomass.

The majority of the literature on biofuel supply chain design assumes all the parameters in the system are known a priori. In biofuel supply chain, however, there is a high level of uncertainty that can be encountered in practice. Hence, it is important to develop approaches to deal with the uncertainties associated with the biofuel supply chain design [19, 36].

A number of recent studies in this field have considered the uncertainties associated with the supply chain. Awudu and Zhang [4] discussed uncertainties in biofuel supply chain management and reviewed related works. A dynamic mixed integer linear programming for strategic design and planning of a supply chain in a period of 10 years was developed by Dal-Mas et al. [8] while considering uncertainty on biomass production cost and product selling price. The objective of their model was to minimize the expected net present value related to each scenario deriving from the combination of corn purchase costs



and fuel ethanol market price. This model was used for the corn-to-ethanol production supply chain in Northern Italy as a test case. Sodhi and Tang [39] introduced a two-stage stochastic model for supply chain management under uncertainty by applying a Stochastic Mixed Integer Non-linear Method. Decisions such as the production topology, plant sizing, product selection, product allocation are considered. Kim et al. [26] proposed a two-stage mixed integer stochastic model to determine the size and location of the biorefineries. To design the problem in a manageable size, they considered only the bounds of the parameters. Marvin et al. [30] considered a mixed integer linear programming to determine optimal locations and capacities of biorefineries with biomass harvest and distribution. They also performed sensitivity analysis to verify the impact of price uncertainty on the decisions. Giarola et al. [18] general mixed integer linear programming modelling framework is developed to assess the design and planning of a multiperiod and multi-echelon bioethanol upstream supply chain under market uncertainty considering economic and environmental (global warming potential) performance. Awudu and Zhang [5] proposed a stochastic linear programming model for a biofuel supply chain under demand and price uncertainties within a single-period planning framework to maximize the expected profit. The decisions are to determine the amount of raw materials purchased, the amount of raw materials consumed and the amount of products produced. A simulation model is another useful tool for supply chain management in biofuel industry due to the complexity and degree of uncertainty in such problems [20, 24, 32, 40, 45].

While it has been demonstrated that biofuel industry is more vulnerable to risk compared to many other industries [3], there are only a few studies dealing with the uncertainty in the biofuel supply chain design. The literature reviewed in this paper considered the uncertain parameters while maximizing the profit or minimizing the costs. One of the challenges, however, is to quantify the

adverse impact of the uncertain parameters on demands satisfaction as well as the economic objectives. Feedstock supply is a main source of uncertainty in the biofuel supply chain, because it is highly dependent on the weather and can be negatively affected by pests or diseases. For instance, fluctuation of feedstock supply has a large impact on the level of satisfied biofuel demands. As a consequence, the system may not be able to meet all the demands, or there might be excesses of the supply. In addition, the uncertainty on the selling price of the biofuel, and logistic costs including transportation and operation costs related to the feedstock preparation at the field will directly impact the supply chain system.

In this study, we aim to develop a mathematical modeling framework to design a biorefinery supply chain considering uncertainties in fuel market price, feedstock supply, and logistic costs including transportation and operation costs. Mixed integer programming models with a two-stage stochastic programming approach were applied to address the uncertainties. The first-stage makes the capital investment decisions including the locations and capacities of the biorefineries. Once the first-stage decisions are determined, the second-stage determines the biomass and gasoline flows. The objective function is to maximize the annual profit which is revenue minus costs. Two different types of objectives were considered: expected value of profit,  $E(Profit)$ , and conditional value at risk of profit,  $CVaR(Profit)$ . The proposed models also illustrate the impact of incorporating CVaR in constraints on satisfying demand and controlling the amount of shortage in demand zones.

The rest of the paper is organized as follows: in Section 2.2, the problem statement for biofuel supply chain is presented. Then, we discuss the stochastic programming models for this problem in Section 2.3. In order to highlight the efficiency and applicability of the presented models, a case study in the state of Iowa and the results are presented in Section 2.4. Finally, we conclude the

paper in Section 2.5 with summary of findings.

## 2.2 Problem Statement

The goal of this study is to develop a mathematical modeling framework to design a supply chain network for biofuel considering uncertainty in the system. The biofuel supply chain network consists of biomass production, harvesting, transportation, conversion and fuel distribution. Figure 2.2 shows a schematic structure of the biofuel supply chain. In order to design the supply chain network, we developed two optimization models with different objective functions. These models determine the best locations of the biorefineries to maximize the profit while reducing the risk of biofuel shortages in demand centers. They also specify the amount of biomass transported from harvesting sites to biorefineries as well as the amount of gasoline shipped to the demand nodes.

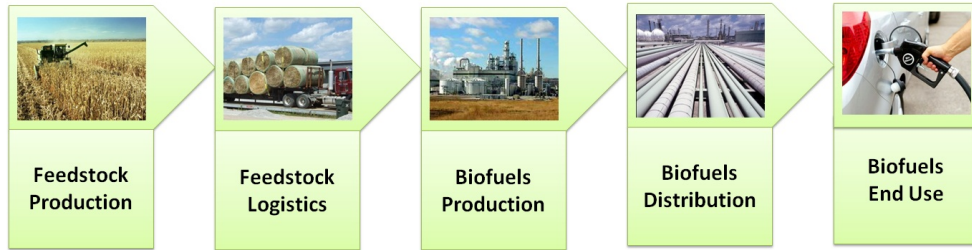


Figure 2.2 Structure of the biofuel supply chain

The parameters used in the problem are defined as follows:

- Set of biomass feedstock harvesting sites;
- Feedstock availability at each harvesting site with the potential fluctuation of yield due to seasonality and weather conditions;
- Sustainability factor for each feedstock harvesting site;
- Feedstock collection and loading cost with a known probability distribution;

- Feedstock transportation cost with a known probability distribution;
- The distance between nodes of the supply chain network based on great circle distance;
- Set of potential biorefineries locations along with the possible set of capacity levels of each one;
- Set of demand zones with the amount of associated demand; and
- Biofuel transportation costs.

Several assumptions are made in the presented models. We assume that the feedstock supply and the logistic costs (including transportation, collection, and loading costs) are uncertain due to high impacts of these parameters on the efficiency of the network [10]. In these models, each biorefinery can be provided by more than one feedstock harvesting site, and each demand can be satisfied by more than one biorefinery. In addition, each harvesting site can serve more than one biorefinery and also each biorefinery can supply more than one demand zone.

The models in this paper are developed to design a biofuel supply chain network to maximize the profit and minimize the costs while controlling the biofuel shortage in demand centers. The objective function of the models is to maximize the total profit (revenue from selling biofuel deducted by total cost including collecting, transporting, and operational costs). The aim is to determine the locations and capacities of biorefineries, and the quantities of biomass feedstock shipped between harvesting sites and biorefineries, as well as the quantities of biofuel transported between biorefineries and demand zones.

## 2.3 Model Formulation

We formulate two stochastic programming models to maximize the profit in a biofuel supply chain network. The uncertainties in the models are defined

with a set of uncertain parameters described by discrete distributions. Scenarios are generated based on the combination of the uncertain parameters. A two-stage stochastic programming approach was incorporated to investigate the decision making under the uncertainties. The fundamental idea behind two-stage stochastic programming is the concept of recourse, which is the ability to take corrective action after a realization of a scenario. The first-stage decisions involve variables that have to be decided before the actual value of uncertainties are realized. After the first-stage, the uncertainties are revealed, and the decision maker must choose an action that optimizes the objectives according to the realization of the scenario. In this problem, the first-stage decision is for the capital investment including the locations and capacities of the biorefineries. The second-stage variables are those that can be determined after the realization of the uncertain parameters. Once the uncertainties of available feedstock is resolved, the second-stage decisions are made, which include the flows of the biomass from harvesting sites to biorefineries and the flows of biofuel to demand zones.

We adopt the concept of Conditional value at Risk (CVaR) in the second objective function and in the constraints as a risk measure to incorporate the uncertainties design setting. As a consequence of uncertainties, there may be biofuel shortage for the demand zones. However, it is not desirable to have a large amount of shortage in a single demand node. Hence, CVaR is employed as a risk measure to control the shortage in each demand zone. The concept of CVaR is also employed in the objective function formulation. Uncertainties in biofuel market price and logistic costs are considered. We consider two different types of objectives: expected value of profit,  $E(Profit)$ , and conditional value at risk of profit,  $CVaR(Profit)$ . In the remainder of this section, we will first explain the concept of CVaR for the loss distribution and the profit distribution. Then, we will elucidate the constraints in the models, and finally, the objective

functions applied in the models are discussed.

### 2.3.1 Value at Risk and Conditional Value at Risk

A common way to incorporate risk-aversion concept into an optimization model is the use of Value at Risk (VaR) constraints. VaR is a popular measure for its comprehensibility, however, because of the conceptual and computational limitations, it is preferred to use Conditional Value at Risk (CVaR) constraints [6, 34, 35].

In this study, we used CVaR constraints to model the risk and uncertainty for the demand shortage. In the definition of VaR and CVaR of a loss function, usually the tail on the *right* side of a probability density function is considered, so in this problem we also use the definition of CVaR for the tail on the right side of a probability density function of fuel demand shortage.

The  $\text{VaR}_{1-\alpha}$  of a random variable of  $X$  is the lowest value of  $t$  such that, with probability  $\alpha$ , the loss will not be more than  $t$ , whereas the  $\text{CVaR}_{1-\alpha}$  is the conditional expectation of loss above that amount  $t$  [35], that is

$$\text{VaR}_{1-\alpha}(X) = \inf \{t : \Pr(X \leq t) \geq 1 - \alpha\},$$

$$\text{CVaR}_{1-\alpha}(X) = E[X | X \geq \text{VaR}_{1-\alpha}].$$

Figure 2.3 depicts the concept of VaR and CVaR of loss or shortage associated with  $\alpha$  percentile for a continuous distribution. Since the stochastic parameters in this study are assumed to be discrete distributed, the demand shortages are defined in a discrete distribution as well. Another representation of  $\text{CVaR}_{(1-\alpha)}$  for a discrete distribution is

$$\text{CVaR}_{1-\alpha}(X) = \inf_t \left\{ t + \frac{1}{\alpha} E[(X - t)_+] \right\} \quad (2.1)$$

where  $(a)_+ = \max\{0, a\}$  [13].

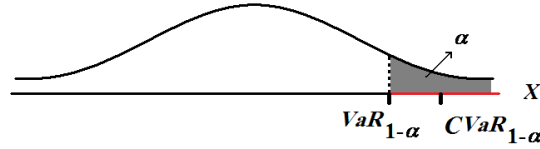


Figure 2.3 CVaR of shortage

In the biofuel supply chain design, CVaR of loss (fuel demand shortage in this study) is chosen as a criterion to control the risk of fuel shortage in demand areas. A constraint which limit the upper bound of the CVaR of demand shortage is incorporated in the model.

Although CVaR is typically defined for an adverse distribution in literature of finance, it can be defined for a favorable distribution such as the distribution of profit. In this study, CVaR is also utilized to incorporate the uncertainty for the profit. For a distribution of the profit, the definition of VaR and CVaR is considered for the tail on the *left* side of a probability density function.

The  $\text{VaR}_{1-\beta}$  of a random variable of  $X$  is the highest value of  $t$  such that, with probability  $\beta$ , the profit will not be less than  $t$ , whereas the  $\text{CVaR}_{1-\beta}$  is the conditional expectation of profit below that amount  $t$ , as follows

$$\text{VaR}_{1-\beta}(X) = \sup \{t : \Pr(X \geq t) \geq 1 - \beta\},$$

$$\text{CVaR}_{1-\beta}(X) = E[X | X \leq \text{VaR}_{1-\beta}].$$

Figure 2.4 shows VaR and CVaR of profit associated with  $\beta$  percentile. For a discrete distribution, another representation of  $\text{CVaR}_{(1-\beta)}$  is

$$\text{CVaR}_{1-\beta}(X) = \sup_t \left\{ t - \frac{1}{\beta} E[(t - X)_+] \right\}. \quad (2.2)$$

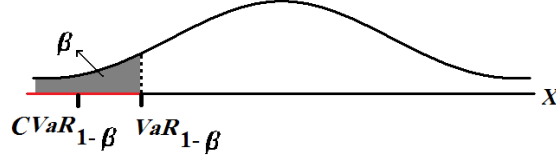


Figure 2.4 CVar of profit

### 2.3.2 Constraints in the Model

In this section, we present a two-stage stochastic programming formulation for biofuel supply chain network design where locations for biorefineries are assumed to be centroid of the counties and demand nodes are based on Metropolitan Statistical Areas (MSAs). We assume that the available feedstock, the price, collection and loading costs, and biomass transportation costs have discrete distribution. Table 2.1 describes the notations used in the model.

The first-stage constraints of the model enforce the selection of biorefinery locations. A set of binary variables,  $\delta_{lj}$ , is defined to determine whether a biorefinery with capacity level of  $l$  is located in a candidate location  $j$ . To ensure that the cost of building biorefineries does not exceed the available budget  $B$ , the following constraint is used:

$$\sum_j \sum_l C_l^B \delta_{lj} \leq B. \quad (2.3)$$

In each candidate location, only one biorefinery can be built, which is specified by the following constraints:

$$\sum_l \delta_{lj} \leq 1, \quad \forall j \in N. \quad (2.4)$$

The rest of the constraints refer to the second-stage decisions which specify the amount of feedstock and biofuel flows among the nodes of the supply chain



Table 2.1 Notations

Scenarios	
$w_s$	Probability that scenario $s$ happens;
$S$	Set of scenarios;
Feedstock Parameters	
$N$	Set of counties producing biomass feedstock;
$A_{is}$	Available feedstock at county $i$ in scenario $s$ ;
$S_i$	Sustainability factor for county $i$
$C_{is}^{SC}$	Variable feedstock collection and loading cost at county $i$ in scenario $s$ ;
Transportation Parameters	
$e$	Material loss factor;
$D_{ij}$	Great circle distance from county $i$ to county $j$ ;
$\tau$	Tortuosity factor;
$C_s^{ST}$	Variable feedstock transportation cost in scenario $s$ ;
Biorefinery Parameters	
$L$	Set of biorefinery levels;
$U_{lj}$	Biorefinery capacity with level $l$ for location $j$ ;
$Y$	Biorefinery fuel process yield;
$C^{GC}$	Unit conversion cost per gallon of biofuel produced;
$B$	Available budget;
$C_l^B$	Cost of opening a biorefinery with level $l$ ;
MSA and Gasoline demand	
$M$	Set of MSAs considered;
$G_k$	Total gasoline demand for MSA $k$ ;
$C^{GT}$	Variable gasoline transportation cost;
$P_{ks}$	Price of gasoline at MSA $k$ for scenario $s$ ;
$sh_{ks}$	Shortage of gasoline demanded at MSA $k$ in scenario $s$ ;
$H$	Upper bound for CVaR of shortage in each MSA;
Optimization Variables	
$\delta_{lj}$	Binary variable that determines if a biorefinery with capacity $l$ is located in county $j$ ;
$f_{ijs}$	Flow of biomass feedstock from county $i$ to county $j$ for refining in scenario $s$ ;
$q_{jks}$	Finished gasoline flow from county $j$ to MSA $k$ in scenario $s$ ;
$\eta, r_s$	Variables defined to formulate CVaR of the shortage.

network based on which scenario happens considering supplies and demands, respectively.

In our models, the biomass supply is assumed to be uncertain with a known distribution from which we take samples, called scenarios and represented by  $S$ . Given the set of counties,  $N$ , that produce biomass feedstock, each county  $i \in N$  has  $A_{is}$  tons per year of corn stover in scenario  $s$  available. A sustainability factor of the corn stover,  $S_i$ , must remain in the field to provide winter cover and prevent soil erosion. Therefore, each county can provide at most  $(1 - S_i)A_{is}$  tons of corn stover per year in scenario  $s$ .

It is assumed that transport distances within one county are negligible in feedstock transportation costs. Each county,  $j \in N$ , can be a candidate for a biorefinery facility with the capacity of  $U_j$ . The flow of the feedstock from biorefinery  $i$  to the biorefinery facility  $j$  in scenario  $s$  is denoted by  $f_{ijs}$ . The total quantity of feedstock transported from county  $i$  can not exceed the amount of feedstock available at the county in each scenario, which is satisfied by

$$\sum_j f_{ijs} \leq (1 - S_i)A_{is}, \quad \forall i \in N, \quad \forall s \in S. \quad (2.5)$$

Capacity constraints are also incorporated in the model. The total flow of feedstock into the biorefinery facility is  $\sum_i^N f_{ijs}$ . The material loss factor  $e_j \in [0, 1)$  accounts for possible losses during loading, transportation, and unloading. And  $e_j \in [0, 1)$  is feedstock dependent. Therefore, the amount of feedstock that can be processed to biofuel at a facility is less than or equal to the capacity,  $U_{lj}$ , in county  $j$  in each scenario, which is denoted by

$$(1 - e_j) \sum_i f_{ijs} \leq \sum_l U_{lj} \delta_{lj}, \quad \forall j \in N, \quad \forall s \in S. \quad (2.6)$$

The biorefineries convert the biomass feedstock into biofuel which will be shipped to the MSAs. Decision variable  $q_{jks}$  represents the quantity of biofuel

shipped from biorefiery  $j$  to the MSA  $k$  under the scenario  $s$ . In a scenario  $s$ , biofuel shipped from biorefineries to a certain MSA  $k$  may not satisfy its demand( $G_k$ ). The shortage is represented by  $sh_{ks}$ , as shown in constraint (7):

$$\sum_j q_{jks} + sh_{ks} = G_k, \quad \forall k \in M, \quad \forall s \in S. \quad (2.7)$$

It is assumed that all the biomass shipped to a biorefinery are converted to biofuel, where  $Y$  is a conversion factor associated to the production yield. This is represented by

$$(1 - e_j) \sum_i f_{ijs} Y = \sum_k q_{jks}, \quad \forall j \in N, \quad \forall s \in S. \quad (2.8)$$

As discussed earlier, the feedstock available to convert to biofuel may not be enough to satisfy all the demands, therefore, there may be shortages in MSAs. To manage the amount of shortages in demand zones, CVaR is employed as a risk measure. The decision makers have the flexibility to determine the limits on the CVaR of shortage which is denoted by  $H$ . Based on the definition of CVaR for a discrete distribution, to enforce a limit on CVaR of shortage associated with  $\alpha$ -quantile, i.e.  $\text{CVaR}_{1-\alpha}(sh) \leq H$ , constraints (9)-(11) are included:

$$\eta + \frac{1}{\alpha} \sum_s w_s r_s \leq H, \quad (2.9)$$

$$r_s \geq sh_{ks} - \eta, \quad \forall k \in M, \quad \forall s \in S, \quad (2.10)$$

$$r_s \geq 0, \quad \forall s \in S. \quad (2.11)$$

Note that these constraints are based on linearization of (2.1) by introducing auxiliary variables  $r_s$  and  $\eta$ .

According to constraints (2.3), we can derive valid inequalities formulated as the following:

$$\sum_j \delta_{lj} \leq \lfloor B/C_l^B \rfloor, \quad \forall l \in L. \quad (2.12)$$

As these constraints make the feasible region tighter, this will facilitate problem solution process, making it more efficiently. This is employed in the case study section.

### 2.3.3 Objective Function

The objective of the models is to maximize the profit which is defined as the revenue from selling the biofuel subtracted by the total cost. Various types of costs are incurred in the biofuel supply chain network. The first one is the unit cost of collection and loading of feedstock shipped and delivered to the biorefinery facilities, which is denoted by  $C_{is}^{SC}$ . The other one is  $C_s^{ST}$  which refers to the unit transportation cost for biomass feedstock. The collection and loading cost and transportation cost are highly dependent on the economic/market conditions, and thus  $C_{is}^{SC}$  and  $C_s^{ST}$  are based on the expected value of the costs. Assuming the distance between county  $i$  and  $j$  as  $D_{ij}$ , the total expected cost of loading, collection, and transportation of biomass feedstock is  $\sum_s (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) w_s f_{ijs}$ . Here  $\tau$  is a tortuosity factor that accounts for the actual distance that must be traveled due to the available geography and transportation infrastructure.

$C^{GC}$  is a unit conversion cost to produce a gallon of biofuel at the biorefinery. The total conversion cost is thus  $\sum_{j,k,s} C^{GC} w_s q_{jks}$ . Biofuel is shipped to the MSA by pipelines at a unit cost of  $C^{GT}$ , so the total biofuel transportation cost equals  $\sum_{j,k,s} D_{jk} C^{GT} w_s q_{jks}$ .

Total capital cost to build the biorefineries is  $\sum_{l,j} C_l^B \delta_{lj}$ . We adopt the amortized capital investment concept. Therefore, the annual payments for a period of  $t = 30$  years with interest rate of  $ir = 8\%$  is:

$$\text{PMT}(\text{Investment}) = \text{Investment} \left( \frac{ir(1+ir)^t}{(1+ir)^t - 1} \right)$$

To compute the profit, we need to calculate the revenue. The expected price biofuel sold at in MSA  $k$  is denoted by  $P_k$ . Therefore, the total revenue obtained by selling the product is  $\sum_{j,k,s} P_k w_s q_{jks}$ . The total profit can be defined as the total revenue subtracted by the total costs.

To maximize the total profit, two modeling approaches are considered. The first is to maximize the expected value of the total profit which is referred to as  $E(\text{Profit})$  in the rest of the paper. The model with objective of  $E(\text{Profit})$  is formulated as follows:

$$\begin{aligned} \max \quad & \sum_{j,k,s} P_{ks} w_s q_{jks} - \sum_{i,j,s} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) w_s f_{ijs} - \sum_{j,k,s} (C^{GC} + D_{jk} C^{GT}) w_s q_{jks} \\ & - \text{PMT}(\sum_{l,j} C_l^B \delta_{lj}) \\ \text{s.t.} \quad & \text{Constraints (2.3) - (2.11),} \\ & f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\ & q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\ & sh_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\ & \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L. \end{aligned}$$

It should be noted that risks associated with profit are not explicitly considered in the first approach with objective of  $E(\text{Profit})$ . Therefore, in the second approach, we adopt the CVaR of profit for objective function to maximize the profit in the cases of unfavorable scenarios.

The goal of the second approach is to maximize the CVaR of the total profit which is referred to as  $\text{CVaR}(\text{Profit})$  in the rest of the paper. In other word,

the objective function can be viewed as maximization of the expected value of  $\beta$ -percentile of the worst case of the total profit. The notation related to the new assumptions are updated in Table 2.2. Variables  $\zeta$  and  $v_s$  are applied to formulate and linearize CVaR of the profit according to the definition of CVaR for the discrete distribution.

Table 2.2 Updated parameters for the stochastic model with objective of  $CVaR(Profit)$

Profit <sub>s</sub>	Total profit for scenario $s$ ;
Revenues	Revenue for scenario $s$ ;
Cost <sub>s</sub>	Total cost for scenario $s$ ;
$\zeta, v_s$	Variables defined to formulate CVaR of the profit.

The model with the objective of  $CVaR(Profit)$  associated with  $\beta$ -percentile is formulated as follows. The objective function used in this model is a linearization of (2.2) by introducing auxiliary variables  $v_s$  and  $\zeta$ .

$$\begin{aligned}
\max \quad & \zeta - \frac{1}{\beta} \sum_s w_s v_s \\
s.t. \quad & v_s \geq \zeta - \text{Profit}_s, \quad \forall s \in S, \\
& v_s \geq 0, \quad \forall s \in S, \\
& \text{Profit}_s = \text{Revenue}_s - \text{Cost}_s, \quad \forall s \in S, \\
& \text{Revenue}_s = \sum_{k,j} P_{ks} q_{jks}, \quad \forall s \in S, \\
& \text{Cost}_s = \sum_{i,j} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) f_{ijs} + \sum_{j,k} (C^{GC} + D_{jk} C^{GT}) q_{jks} \\
& \quad + \text{PMT}(\sum_{l,j} C_l^B \delta_{lj}), \quad \forall s \in S, \\
& \text{Constraints} \quad (2.3) - (2.11), \\
& f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\
& q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& sh_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L.
\end{aligned}$$

## 2.4 Case Study

The stochastic mixed integer linear models proposed in this study are aimed to design a biorefinery supply chain with the consideration of uncertainties. The problem is formulated in two mathematical models with two different objective functions:  $E(\text{Profit})$  and  $CVaR(\text{Profit})$ . The models consider the uncertainties in the fuel market price, feedstock supply, and logistic costs. A novelty in the proposed models is to consider the control of the shortage of biofuel for demand zones based on the CVaR of shortage.

In this case study, we examine the supply chain network design for conversion of biomass into biofuel in the state of Iowa. Biomass can be harvested

and collected in every county in the state. The feedstock is then transported from county centroid to the biorefineries for conversion to biofuel. The biofuel is transported to the demand areas, which are based on the MSAs in Iowa. It is assumed that the transportation distance within the county has a negligible effect on feedstock transportation costs. The goal is to determine the optimal biorefineries locations and capacities with the objective of maximizing the annual profit while controlling the risk of the biofuel shortages at the MSAs.

In this section, we first explain the data used in this case study. Then, we analyze and discuss the model output and draw managerial insights for biofuel supply chain network design.

#### 2.4.1 Data Sources for the Case Study

In the state of Iowa, there are 99 counties which are potential biomass harvesting locations. Each county is also considered as a candidate location to build a biorefinery with capacity level of 1000, 1500 or 2000 ton per day for the conversion to biofuel. The maximum available budget assigned to this project is \$3,000,000,000. We consider 21 MSAs in Iowa as the demand areas. Biofuel demand at each MSA is estimated as a percent of the state-level gasoline consumption as provided by Energy Information Administration (EIA). This percent is based on the ratio of the population within the MSA and the total population of the state.

The confidence levels to define the CVaR of shortage  $\alpha$  and CVaR of profit  $\beta$  are both assumed to be 20% in this case study. The impacts of different confidence levels is not within the scope of this study. The upper bound for biofuel shortage at MSAs is assumed to be  $H = 200,000,000$  gallons per year.

Material loss factor  $e$ , which accounts for possible losses during loading, transportation, and unloading, is assumed to be 0.05. Tortuosity factor  $\tau$  is considered 1.29, which is multiplied by distances and shows the actual distances



that must be traveled according to the geographical infrastructure. Based on the experimental data, the biorefinery process yield of feedstock,  $Y$ , is assumed to be 0.218. The sustainability factors,  $S_i$ , to be 0.718 at all counties [44].

In this case study, the scenarios are generated based on the average values of the parameters and their deviation according to the historical records. We considered 16 scenarios for available feedstock, 3 scenarios for price of gasoline, 2 scenarios for feedstock collection and loading costs, and 2 scenarios for transportation cost. Tables 2.3-2.6 list possible scenarios and their probabilities considered for each parameter. The combination of these scenarios constructs 192 scenarios in total for this problem.

Table 2.3 Scenarios for available feedstock

Scenario	Available feedstock	Probability
Scenario 1	$A - 8\%A$	1/16
Scenario 2	$A - 7\%A$	1/16
Scenario 3	$A - 6\%A$	1/16
Scenario 4	$A - 5\%A$	1/16
Scenario 5	$A - 4\%A$	1/16
Scenario 6	$A - 3\%A$	1/16
Scenario 7	$A - 2\%A$	1/16
Scenario 8	$A - 1\%A$	1/16
Scenario 9	$A + 1\%A$	1/16
Scenario 10	$A + 2\%A$	1/16
Scenario 11	$A + 3\%A$	1/16
Scenario 12	$A + 4\%A$	1/16
Scenario 13	$A + 5\%A$	1/16
Scenario 14	$A + 6\%A$	1/16
Scenario 15	$A + 7\%A$	1/16
Scenario 16	$A + 8\%A$	1/16

#### 2.4.2 Results Analysis and Discussion

The proposed models aim to determine capital investment decisions on the location and capacities of the biorefineries, the feedstock transportation and biofuel delivery decisions. The first-stage decisions have to be made before

Table 2.4 Scenarios for price of gasoline

Scenario	Price of gasoline	Probability
Scenario 1	$P - 10\%P$	1/3
Scenario 2	$P$	1/3
Scenario 3	$P + 10\%P$	1/3

Table 2.5 Scenarios for feedstock collection and loading cost

Scenario	Feedstock collection and loading cost	Probability
Scenario 1	$C^{SC} - 10\%C^{SC}$	1/2
Scenario 2	$C^{SC} + 10\%C^{SC}$	1/2

the uncertainties are realized, and the second-stage decisions are made after the realization of the system parameters. In this study, the first-stage decisions include the capital investment decisions (the location and capacities of the biorefineries). Once the uncertainties are realized, the second-stage decisions are made which include the flows of the biomass from harvesting sites to biorefineries and the flows of biofuel to demand areas. The uncertainties considered in this problem consist of feedstock supply, fuel market price, and logistic costs. Two modeling approaches are adopted in the objective function formulation: expected value and CVaR of profit. In the first approach, the objective function is to maximize the expected value of profit. The profit of the project is an important performance measure to evaluate the effectiveness of the decision. However, the expected profit approach does not explicitly address the risk of decision making under the unfavorable events. In order to manage the system risks, we adopted CVaR of profit as the second approach in the objective function.

It should be noted that it is of great importance to control the shortage of demand in the system. One of the challenges in this model is incurring a large amount of shortage in a single demand MSA. We design a risk measure in the

Table 2.6 Scenarios for transportation cost

Scenario	Transportation cost	Probability
Scenario 1	$C^{ST} - 10\%C^{ST}$	1/2
Scenario 2	$C^{ST} + 10\%C^{ST}$	1/2

constraints to level the shortage and decrease the probability of larger shortage occurring in the network. We consider CVaR of the shortage and set an upper bound on that to control the risk of shortage through demand areas.

In the case study, the state of Iowa is selected due to the data availability to demonstrate the effectiveness and applicability of the proposed modeling framework. There are 99 counties in Iowa with biomass feedstock supply, each of which is considered as a candidate location for biorefinery. The demand zones are 21 MSAs located in the state. We implemented the proposed models with different assumptions in the case study to compare and analyze the results: the model with objective function of  $E(Profit)$  with and without the CVaR constraints on the shortage, and also the model with objective function of  $CVaR(Profit)$  with and without the CVaR constraints on the shortage.

We implement two proposed models in this case study and compare them to the models with the same assumption but without considering CVaR constraints on shortages. Model (A) refers to the model with the objective of  $E(Profit)$ , and Model (B) is the model with the objective of  $CVaR(Profit)$ . These models are implemented in CPLEX Python API version 12.2.

- In Model (A), the objective is to maximize  $E(Profit)$ . At first, we implement this model while there are no control on the shortage of demand. The version of model (A) without considering the constraints on shortages is as follows:

$$\begin{aligned}
\max \quad & \sum_{j,k,s} P_{ks} w_s q_{jks} - \sum_{i,j,s} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) w_s f_{ijs} - \sum_{j,k,s} (C^{GC} + D_{jk} C^{G,T}) w_s q_{jks} \\
& - \text{PMT}(\sum_{l,j} C_l^B \delta_{lj}) \\
s.t. \quad & \text{Constraints (2.3) -- (2.8),} \\
& \text{Constraints (2.12),} \\
& f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\
& q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& sh_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L.
\end{aligned}$$

Figure 2.5 shows the results from model (A) without considering shortage constraints. As shown in Figure 2.5, there is a large amount shortage in one MSA, that is about 528,000 gallons per year. This motivated the use of a risk measure to control the shortage through MSAs.

- Model A which considers CVaR constraints on the shortage is formulated as follows:

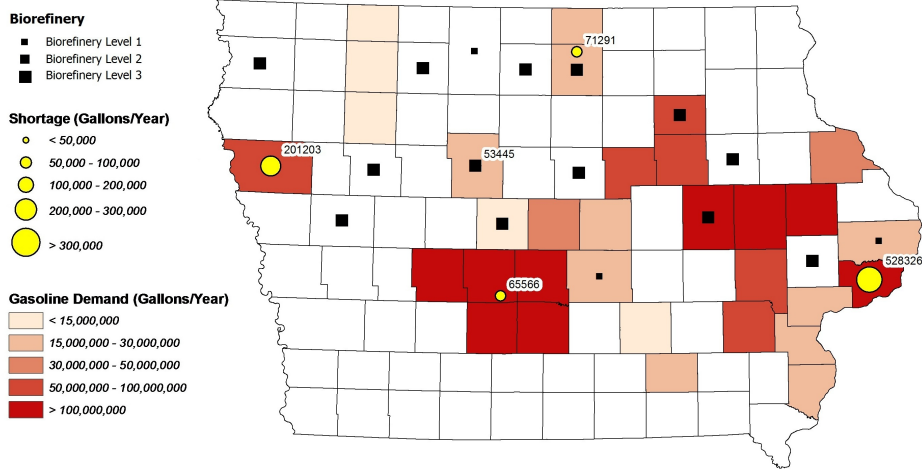


Figure 2.5 Biorefineries locations for the model with the objective of  $E(Profit)$  (Model A) without considering CVaR constraints on shortage of demand

$$\begin{aligned}
 \max \quad & \sum_{j,k,s} P_{ks} w_s q_{jks} - \sum_{i,j,s} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) w_s f_{ijs} - \sum_{j,k,s} (C^{GC} + D_{jk} C^{G,T}) w_s q_{jks} \\
 & - \text{PMT}(\sum_{l,j} C_l^B \delta_{lj}) \\
 s.t. \quad & \text{Constraints (2.3) - (2.12),} \\
 & f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\
 & q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
 & sh_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
 & \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L.
 \end{aligned}$$

Figure 2.6 shows that when we add CVaR constraints on the shortage to the model with the objective of  $E(Profit)$ , the shortages are split in a more reasonable way, such that the system will not incur that large amount of shortage in any single MSA. It should be noted that the number of MSAs with biofuel shortage is increased. In other word, after incorporating the

CVaR constraints on the shortage, the system shortage is more dispersed in the system which mitigate the system risks. In addition, after incorporating constraints (2.9)-(2.11) the total amount of shortage decreases in this model. This is due to the limit forced on the shortage. In this model, the expected value of profit decreased about 4% due to the additional constraints added to the model.

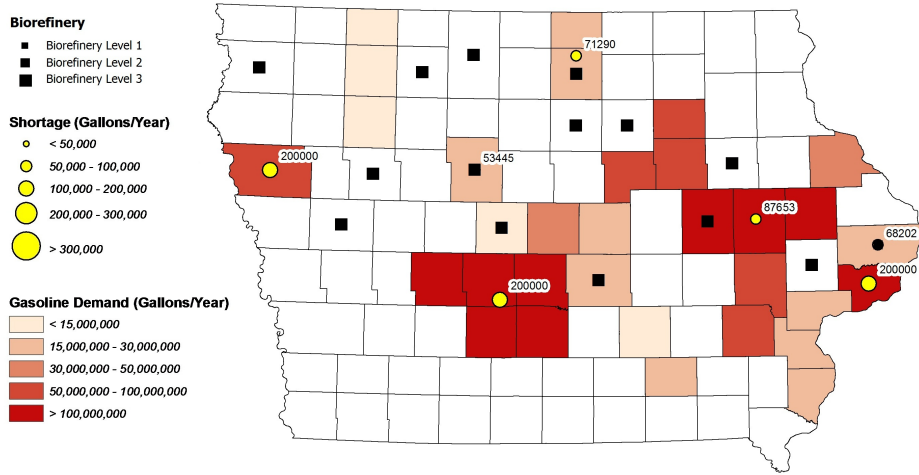


Figure 2.6 Biorefineries locations for the model with the objective of  $E(Profit)$  (Model A) with considering CVaR constraints on shortage of demand

- Model (B) considers the objective of  $CVaR(Profit)$ . The following formulation refers to this model while there is no control on the biofuel shortages:

$$\begin{aligned}
\max \quad & \zeta - \frac{1}{\beta} \sum_s w_s v_s \\
s.t. \quad & v_s \geq \zeta - \text{Profit}_s, \quad \forall s \in S, \\
& v_s \geq 0, \quad \forall s \in S, \\
& \text{Profit}_s = \text{Revenue}_s - \text{Cost}_s, \quad \forall s \in S, \\
& \text{Revenue}_s = \sum_{k,j} P_{ks} q_{jks}, \quad \forall s \in S, \\
& \text{Cost}_s = \sum_{i,j} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) f_{ijs} + \sum_{j,k} (C^{GC} + D_{jk} C^{GT}) q_{jks} \\
& \quad + \text{PMT}(\sum_{l,j} C_l^B \delta_{lj}), \quad \forall s \in S, \\
& \text{Constraints} \quad (2.3) - (2.8), \\
& \text{Constraints} \quad (2.12), \\
& f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\
& q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& sh_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L.
\end{aligned}$$

According to Figure 2.7, the results show that the amounts of shortage are very large in three MSAs. The total amount of shortages is more than total shortages in Model (A). The reason is that Model (A) tries to maximize the expected profit without the risk control of unfavorable events in the objective function; however, Model (B) attempts to maximize the profit in the averse conditions which is associated with the system risks.

- Now we consider Model (B) while enforcing an upper bound on CVaR of shortage in order to avoid concentrated biofuel shortages for the MSAs. This model is formulated as:

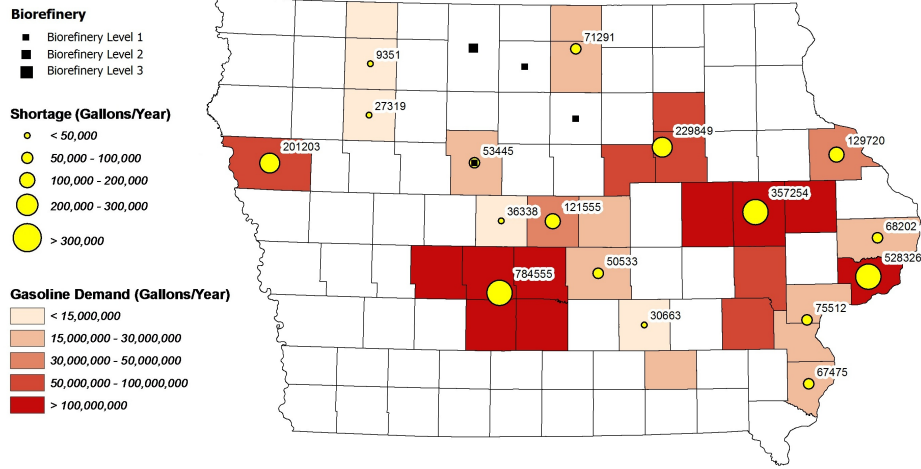


Figure 2.7 Biorefineries locations for the model with the objective of  $CVaR(Profit)$  (Model B) without considering CVaR constraints on shortage of demand

$$\begin{aligned}
\max \quad & \zeta - \frac{1}{\beta} \sum_s w_s v_s \\
s.t. \quad & v_s \geq \zeta - \text{Profit}_s, \quad \forall s \in S, \\
& v_s \geq 0, \quad \forall s \in S, \\
& \text{Profit}_s = \text{Revenue}_s - \text{Cost}_s, \quad \forall s \in S, \\
& \text{Revenue}_s = \sum_{k,j} P_{ks} q_{jks}, \quad \forall s \in S, \\
& \text{Cost}_s = \sum_{i,j} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) f_{ijs} + \sum_{j,k} (C^{GC} + D_{jk} C^{GT}) q_{jks} \\
& \quad + \text{PMT}(\sum_{l,j} C_l^B \delta_{lj}), \quad \forall s \in S, \\
& \text{Constraints} \quad (2.3) - (2.12), \\
& f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\
& q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& sh_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L.
\end{aligned}$$



The results from the model with objective of  $CVaR(Profit)$  with the CVaR of shortage constraints is shown in Figure 2.8. When we add the CVaR of shortage constraints, the amount of shortage in a single MSA is dispersed which is similar to Model (A). As shown in Figure 2.8, although we have more MSAs with shortage, we do not have any concentrated shortage in a single MSA as we had from Model (B) without CVaR constraints. Moreover, the total shortage is less than the same model without considering CVaR constraints on the shortage.

After applying the constraints on the shortage in this model, the expected value of profit increased about 8% although the objective value (i.e. CVaR of profit) decreased due to the additional constraints. However, model B resulted in smaller profit compared to model A. This is because that model B tries to improve the profit in the worst cases, while model A aims to maximize the expected value of profit.

The observations from both models indicate that using CVaR constraints is a reasonable approach to address the risk of the shortage. It can be applied in the system in which the risk of occurring large amounts of shortage in a single MSA is expensive. The reason is that the constraints of the model make the inevitable shortage to be split through all the MSAs according to parameter  $\alpha$  in the CVaR, and therefore it is not allowed to have a large amount of shortage in a single MSA. In addition, comparison of Model A and B, regardless of CVaR constraints, shows that model B is more appropriate for more conservative decision makers because of the property of risk-aversion embedded in its objective function. This risk aversion property can be set according to the decision maker preference by changing parameter  $\beta$  in the CVaR, in the objective function. As stated before, studying changes in parameter  $\alpha$  and  $\beta$  was not included in the scope of this study.

In summary, comparisons between models with two different objective functions indicates that unsurprisingly the models with the objective function of  $E(Profit)$  provide smaller shortages, whereas the models with the objective function of  $CVaR(Profit)$  yield larger shortages. In addition, models without the CVaR constraints on the shortage result in a larger concentrated amount of shortages in the MSAs which is due to that there is no upper bound on the amount of shortage in a specific demand area. However, the models with CVaR constraints on the shortage, result in more MSAs with shortages, but the amount of shortage in each MSA is reduced. In other words, enforcing an upper bound on the CVaR of the shortage prevent the occurrence of a large amount of shortage in a single MSA. This result is as expected, as the CVaR constraints set a limit on the amount of shortage in a single MSA.

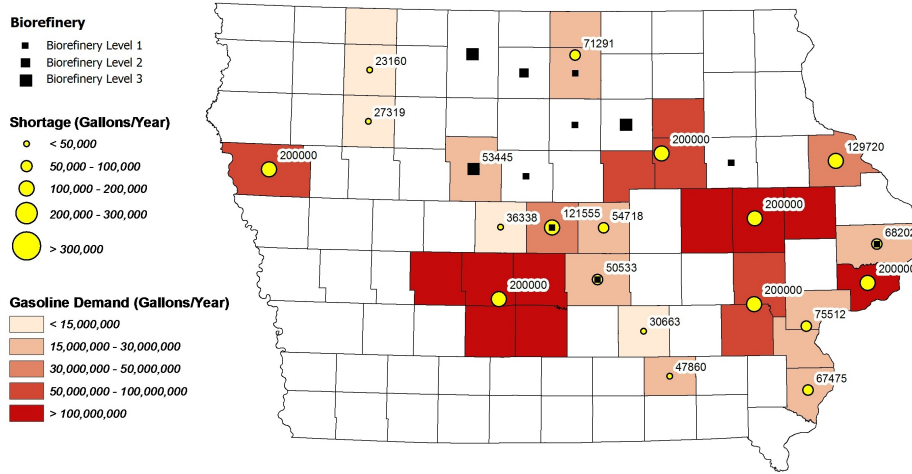


Figure 2.8 Biorefineries locations for the model with the objective of  $CVaR(Profit)$  (Model B) with considering CVaR constraints on shortage of demand

## 2.5 Conclusion

Biofuels play an important role in providing clean and secure energy and promoting economic growth. One of the most important and challenging issues of biofuel production is biofuel supply chain network design. The general structure of biofuel supply chain consists of biomass production, harvesting, transportation, conversion and fuel distribution. The biomass is harvested at the farms and shipped to the biorefineries. At biorefineries, the feedstock is converted to biofuel and then transported to demand areas. In the research arena of biofuel supply chain network design, one of the biggest challenges is to deal with uncertainties along the supply chain.

The goal of this study is to explore the design of a biofuel supply chain network under uncertainty. We proposed a mathematical programming framework with the approach of two-stage stochastic programming to determine capital investment decisions on the location and capacities of the biorefineries, the feedstock transportation and biofuel delivery decisions. The uncertainties considered in this problem consist of feedstock supply, fuel market price, and logistic costs. Two modeling approaches are adopted in the objective function formulation: expected value and CVaR of profit.

To sum up, this study provided a mathematical modeling framework to the biofuel supply chain network design under uncertainty. Two types of objective functions: expected value of profit and CVaR of profit were considered. The first approach focuses on maximize the expected profit where the latter approach is more on the mitigation of system risk under averse conditions. The impacts of incorporating the stochastic shortage control are also investigated by incorporating the CVaR of shortage as a constraint in the model.

We conclude the paper by pointing out two future research directions. Biofuel supply chain network design depends on many parameters and factors. However, the proposed method only provides a basic framework to study the

biofuel supply chain under uncertainty. It is suggested to extend these models to consider additional operational assumptions in future studies. In addition, the larger the number of scenarios, the more accurate the decisions would be. Consequently, the computational complexity would substantially increase. Therefore, exploring more efficient algorithms to solve the problem could be another direction for future work in this area.

# CHAPTER 3. EVALUATION OF THE IMPACTS OF POLICIES ON THE BIOFUEL SUPPLY CHAIN DESIGN UNDER UNCERTAINTY

Narges Kazemzadeh<sup>1</sup> and Guiping Hu<sup>2</sup>

Department of Industrial and Manufacturing Systems Engineering, Iowa State  
University, Ames, IA 50011, USA

## Abstract

Biofuel industry has attracted much attention due to its potential to reduce the dependency on fossil fuels and contribute to the renewable energy. The Renewable Fuel Standard (RFS) sets policies and mandates to support the production and consumption of biofuels. However, the uncertainty associated with these policies and regulations of biofuel production and consumption have significant impacts on the biofuel supply chain network. This study aims to determine the optimal design of the biofuel supply chain to maximize annual profit under the impacts of governmental policies. In this study, two-stage stochastic programming models are developed in which conditional value at risk is considered as a risk measure to control the shortage of mandate. A case study in Iowa is conducted to investigate the effects of different policies and demonstrate the applicability and efficiency of the models.

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<sup>1</sup>kazemzad@iastate.edu

<sup>2</sup>gphu@iastate.edu

**keywords**

supply chain management, biorefinery, stochastic programming, biofuel policy, CVaR

**3.1 Introduction**

Biofuels are of growing interest for reasons of the environmental and economic benefits. Most important advantages of biofuels are its potential to reduce the dependency on fossil fuel and promote the rural development in agricultural regions, and sustainability as well as greenhouse gas mitigation [15]. Biomass has also the advantage to provide solid, liquid and gaseous fuels that can be stored, transported and utilized, far away from the source [11].

The development of the global biofuel production over the last decade significantly relies on the supporting policies. The United States is currently the largest biofuel producer. Over the past years, different policies have been introduced to support the production and consumption of biofuels in the US [14]. These policies are often necessary to successfully promote biofuel production since advanced biofuels are often not competitive comparing with fossil fuels. In the United States, ambitious support policies have recently been adopted that include explicit measures to encourage usage of second-generation biofuels [15, 31].

U.S. Environmental Protection Agency (EPA) has proposed rules in a Renewable Fuel Standard (RFS) that governs how biofuels are produced and used in the U.S. The RFS originated with the Energy Policy Act of 2005 and was expanded and extended by the Energy Independence and Security Act of 2007 (EISA) [31]. Among the various policy instruments, blending mandates are a common measure to ensure a certain amount of biofuel is consumed, thereby offering more market certainty to the producer side. The United States is the only country so far to have adopted a blending mandate for the second-

generation biofuels. The RFS defines the volume of different biofuels that have to be blended with conventional fuel between 2006 and 2022 [15].

Currently the major share of biofuel in the United States is ethanol produced from corn, which has been strongly supported by the existing policies. The total volume of biofuels mandated in the RFS increases from 15 billion litres in 2006 to 136 billion litres in 2022 as shown in Figure 3.1.

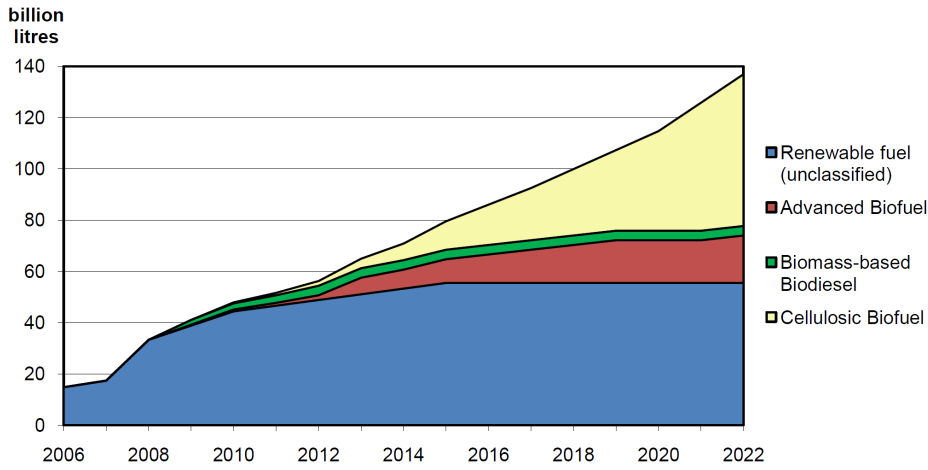


Figure 3.1 Biofuel mandate in the United States Renewable Fuel Standard (Source: [15])

One of the most important aspects of the biofuel production planning is the design of biomass supply chain networks. In the literature, there are numerous studies devoted to the supply chain design of biorefineries [16, 42, 28]. It has been demonstrated that biofuel industry has been challenged by the significant uncertainties along the biofuel supply chain such as the available feedstock supply, because it is highly dependent on the weather and can be negatively affected by pests or diseases [3]. Hence, a large amount of studies in this area through recent years considered the uncertainties associated with the supply chain [4, 8, 39, 26, 30, 18, 5, 25].

The government regulations and policies affect the production and use of biofuel across the biofuel supply chain. Therefore, it is of great importance to consider the impacts of these policies on the total profit in the biofuel supply

chain design problem. Hoekman [21] summarized policy and regulatory drivers for biofuels in the U.S., described the usage trends and projections, and highlighted major R&D efforts to promote development and commercialization of the second generation biofuels. De Gorter and Just [9] claimed that at least 65% of total world fuel consumption is affected by tax credits for biofuels. De Gorter et al. [10] evaluated the economic effects of an import tariff with or without mandates and/or tax credits. It is shown that tax credit and mandate result in significant changes in the price of biofuel.

The goal of this study is to investigate the impacts of biofuel policies on the biofuel supply chain models under uncertainty. One of the important policies we consider in this study is renewable fuel standard mandate. The Renewable Identification Number (RIN) system was developed by the U.S. Environmental Protection Agency (EPA) to ensure the compliance with RFS mandates. Each year, obligated parties are required to meet their prorated shares of the RFS mandates by accumulating RINs, either through fuel blending or by purchasing RINs from others. Another biofuel policy is Tax credit which makes blenders more willing to blend biofuels. Pass-through quantifies how much each stakeholder gets when a subsidy or tax credit is provided. The impact of the uncertainty regarding the pass-through play an important role in biofuel industry. The effects of pass-through on the biofuel supply chain models are also investigated in this study.

The mathematical modeling framework considered in this study aims to design a biorefinery supply chain considering the uncertainties in the fuel market price, feedstock supply, and logistic costs including the transportation and operation costs. Two mixed integer programming models with the two-stage stochastic programming approach were applied to address the uncertainties. The first-stage makes the capital investment decisions including the locations and capacities of the biorefineries, and once the uncertainties of available feed-



stock is resolved the second-stage determines the biomass and gasoline flows. The objective function is to maximize the annual profit for biofuel producers. Two different types of objectives were considered: expected value of profit,  $E(Profit)$ , and conditional value at risk of profit,  $CVaR(Profit)$ . The proposed models also illustrate the impact of incorporating CVaR in constraints on satisfying demand and controlling the amount of shortage of mandate in demand zones.

The rest of the paper is organized as follows: in Section 3.2, we discuss the problem statement for biofuel supply chain, and then, the stochastic programming models updated for this problem under biofuel policies are reviewed. A case study in the state of Iowa are presented in Section 3.3 in order to compare the results and highlight the impacts of the policies. Finally, we conclude the paper in Section 3.4 with the summary of findings.

### 3.2 Problem Statement and Model Formulation

The biofuel supply chain network consists of biomass production, harvesting, transportation, conversion and fuel distribution. The goal of this study is to investigate the impacts of policies in the biofuel supply chain network design. The base of the proposed models in this paper is the mathematical modeling framework presented in [25]. We consider the optimization models to determine the best locations of the biorefineries with the two different objective functions on maximizing the profit. They also specify the amount of biomass transported from harvesting sites to biorefineries as well as the amount of gasoline shipped to the demand nodes. In this work, we focus on the impacts of the biofuel policies on the network.

Important parameters involved in the problem consist of the biomass feedstock harvesting sites, potential biorefineries locations along with the capacity levels, and demand zones with the amount of associated mandate. There are

also important factors such as percentage of mandate enacted, percentage of pass-through, sustainability, etc. Uncertain parameters include the costs related to the biomass feedstock, and also feedstock availability at each harvesting site with the potential fluctuation of yield due to the seasonality and weather conditions.

We made several assumptions in the model formulation. The uncertainties in the models are defined with a set of uncertain parameters described by discrete distributions. Scenarios are generated based on the combination of the uncertain parameters. The uncertain parameters consist of the feedstock supply and the logistic costs including transportation, collection, and loading costs. Credit and cost from RINs and pass-through are also considered in the model. The biorefineries with three possible capacity level and associated investment costs can be built in a candidate location. We assume that each biorefinery can be provided by more than one feedstock harvesting site, and each demand can be satisfied by more than one biorefinery. In addition, each harvesting site can serve more than one biorefinery and also each biorefinery can supply more than one demand zone.

The goal of these models are to design a biofuel supply chain network to maximize the profit and minimize the costs while satisfy the biofuel mandates and controlling the biofuel shortage for the mandates. These models determine the locations and capacities of biorefineries, and the quantities of biomass feedstock shipped between harvesting sites and biorefineries, as well as the quantities of biofuel transported between biorefineries and demand zones. The objective function of the models is to maximize the total profit for all the refineries. The revenue can be obtained from selling biofuel, pass-through and credit form RINs, and the total cost consists of collecting, transporting and operational, and shortage costs.

In this problem, locations for biorefineries are assumed to be centroid of

the counties and demand nodes are based on Metropolitan Statistical Areas (MSAs). Table 3.1 describes the notations used in the model.

### 3.2.1 Constraints in the Model

In this model, the following two sets of constraints are related to the first-stage decisions, that is the selection of biorefinery locations, and the others are dedicated to the second-stage decisions which specify the amount of feedstock and biofuel flows in the system.

A set of binary variables,  $\delta_{lj}$ , is defined to determine whether a biorefinery with capacity level of  $l$  is located in a candidate location  $j$ . The following constraint is used to ensure that the cost of building biorefineries does not exceed the available budget  $B$ :

$$\sum_j \sum_l C_l^B \delta_{lj} \leq B. \quad (3.1)$$

The next constraints shows that at most biorefinery can be built in each candidate location:

$$\sum_l \delta_{lj} \leq 1, \quad \forall j \in N. \quad (3.2)$$

We assumed that the biomass supply is uncertain with a known distribution. Scenarios are designed based on the distribution and represented by  $S$ . Given the set of counties,  $N$ , that produce biomass feedstock, each county  $i \in N$  has  $A_{is}$  tons per year of corn stover in scenario  $s$  available. Given  $S_i$  as the sustainability factor of the corn stover, each county can provide at most  $(1 - S_i)A_{is}$  tons of corn stover per year in scenario  $s$ . The flow of the feedstock from biorefinery  $i$  to the biorefinery facility  $j$  in scenario  $s$  is denoted by  $f_{ijs}$ . The following constraints ensure that the total quantity of feedstock transported

Table 3.1 Notations

Scenarios	
$w_s$	Probability that scenario $s$ happens;
$S$	Set of scenarios;
Feedstock Parameters	
$N$	Set of counties producing biomass feedstock;
$A_{is}$	Available feedstock at county $i$ in scenario $s$ ;
$S_i$	Sustainability factor for county $i$
$C_{is}^{SC}$	Variable feedstock collection and loading cost at county $i$ in scenario $s$ ;
Transportation Parameters	
$e$	Material loss factor;
$D_{ij}$	Great circle distance from county $i$ to county $j$ ;
$\tau$	Tortuosity factor;
$C_s^{ST}$	Variable feedstock transportation cost in scenario $s$ ;
Biorefinery Parameters	
$L$	Set of biorefinery levels;
$U_{lj}$	Biorefinery capacity with level $l$ for location $j$ ;
$Y$	Biorefinery fuel process yield;
$C^{GC}$	Unit conversion cost per gallon of biofuel produced;
$B$	Available budget;
$C_l^B$	Cost of opening a biorefinery with level $l$ ;
MSA and Gasoline mandate	
$M$	Set of MSAs considered;
$G_k$	Total gasoline mandate for MSA $k$ ;
$C^{GT}$	Variable gasoline transportation cost;
$P_{ks}$	Price of gasoline at MSA $k$ for scenario $s$ ;
$sh_{ks}$	Shortage of gasoline mandated at MSA $k$ in scenario $s$ ;
$sp_{ks}$	Surplus of gasoline mandated at MSA $k$ in scenario $s$ ;
$H$	Upper bound for CVaR of shortage in each MSA;
$\lambda$	Percentage of gasoline mandate;
$\gamma$	Percentage of pass-through;
$X$	Tax credit for every gallon of biofuel;
$RIN$	Value of RIN;
Optimization Variables	
$\delta_{lj}$	Binary variable that determines if a biorefinery with capacity $l$ is located in county $j$ ;
$f_{ijs}$	Flow of biomass feedstock from county $i$ to county $j$ for refining in scenario $s$ ;
$q_{jks}$	Finished gasoline flow from county $j$ to MSA $k$ in scenario $s$ ;
$\eta, r_s$	Variables defined to formulate CVaR of the shortage.

from county  $i$  does not exceed the amount of feedstock available at the county in each scenario:

$$\sum_j f_{ijs} \leq (1 - S_i)A_{is}, \quad \forall i \in N, \quad \forall s \in S. \quad (3.3)$$

Each county,  $j \in N$ , can be a candidate for a biorefinery facility with the capacity of  $U_j$ . The amount of feedstock that can be processed to biofuel at a facility is less than or equal to the specified capacity, which is ensured by

$$(1 - e_j) \sum_i f_{ijs} \leq \sum_l U_{lj} \delta_{lj}, \quad \forall j \in N, \quad \forall s \in S. \quad (3.4)$$

The biofuel produced in the biorefineries will be shipped to the MSAs. Decision variable  $q_{jks}$  represents the quantity of biofuel shipped from the biorefinery  $j$  to the MSA  $k$  under the scenario  $s$ . Variable  $sh_{ks}$  represents the shortage of biofuel mandate, while  $sp_{ks}$  represents the surplus of biofuel mandate in MSA  $k$  and scenario  $s$ . The following constraints shows the relation between quantity of biofuel, shortage, surplus and biofuel mandate:

$$\sum_j q_{jks} + sh_{ks} - sp_{ks} = \lambda_s G_k, \quad \forall k \in M, \quad \forall s \in S. \quad (3.5)$$

We assumed that all the biomass shipped to a biorefinery are converted to biofuel, where  $Y$  is a conversion factor associated to the production yield. This is represented by

$$(1 - e_j) \sum_i f_{ijs} Y = \sum_k q_{jks}, \quad \forall j \in N, \quad \forall s \in S. \quad (3.6)$$

One of the features of the proposed models is the adoption of Conditional Value at Risk (CVaR) [6, 34, 35] to incorporate risk-aversion concept into an

optimization model. The definition of Value at Risk (VaR) and CVaR are illustrated below.

The  $\text{VaR}_{1-\alpha}$  of a random variable of  $X$  is the lowest value of  $t$  such that, with probability  $\alpha$ , the loss will not be more than  $t$ , whereas the  $\text{CVaR}_{1-\alpha}$  is the conditional expectation of loss above that amount  $t$  [35], that is

$$\begin{aligned}\text{VaR}_{1-\alpha}(X) &= \inf \{t : \Pr(X \leq t) \geq 1 - \alpha\}, \\ \text{CVaR}_{1-\alpha}(X) &= E[X | X \geq \text{VaR}_{1-\alpha}].\end{aligned}$$

Another representation of  $\text{CVaR}_{(1-\alpha)}$  for a discrete distribution is

$$\text{CVaR}_{1-\alpha}(X) = \inf_t \left\{ t + \frac{1}{\alpha} E[(X - t)_+] \right\} \quad (3.7)$$

where  $(a)_+ = \max\{0, a\}$  [13].

We applied CVaR as a risk measure in order to control the amount of shortage of biofuel mandates. Parameter  $H$  is defined as a limit on the CVaR of shortage of the mandates. Constraints (3.8)-(3.10) enforce a limit on CVaR of shortage associated with  $\alpha$ -quantile. In other words, constraints (3.8)-(3.10) are the linearization of  $\text{CVaR}_{1-\alpha}(sh) \leq H$  by introducing auxiliary variables  $r_s$  and  $\eta$ :

$$\eta + \frac{1}{\alpha} \sum_s w_s r_s \leq H, \quad (3.8)$$

$$r_s \geq sh_{ks} - \eta, \quad \forall k \in M, \quad \forall s \in S, \quad (3.9)$$

$$r_s \geq 0, \quad \forall s \in S. \quad (3.10)$$

In addition, a set of valid inequalities derived from constraints (2.3) are included in the model, as formulated in the following:

$$\sum_j \delta_{lj} \leq \lfloor B/C_l^B \rfloor, \quad \forall l \in L. \quad (3.11)$$

### 3.2.2 Objective Function

In these models the objective is to maximize the annual profit which is defined as the total revenue subtracted by the total cost. The total revenue consist of revenue from selling the biofuel, pass-through revenue, as well as credits from selling excess RINs, and different kinds of costs considered in the biofuel supply chain network are collection and loading cost, transportation cost, conversion cost, shortage cost and capital cost.

Three different sources of revenues are considered in the models: revenue from selling the biofuel, pass-through revenue, and credits from selling excess RINs. The expected price biofuel sold at in MSA  $k$  is denoted by  $P_{ks}$ . Therefore, the revenue obtained by selling the product is  $\sum_{j,k,s} P_{ks} w_s q_{jks}$ . The revenue from pass-through is  $\sum_{j,k,s} X \gamma w_s q_{jks}$  in which  $X$  represents the tax credit for every gallon of biofuel, and  $\gamma$  is the percentage of pass-through. The credit obtained from surplus production of biofuel is calculated by  $\sum_{k,s} w_s s p_{ks} RIN$ .

There are also different types of costs incurred in the biofuel supply chain network including collection and loading cost, transportation cost, conversion cost, capital cost and shortage cost. Unit cost of collection and loading of feedstock shipped and delivered to the biorefiery facilities is denoted by  $C_{is}^{SC}$ . Unit transportation cost for biomass feedstock is specified by  $C_s^{ST}$ . Assuming the distance between county  $i$  and  $j$  as  $D_{ij}$ , the total expected cost of loading, collection, and transportation of biomass feedstock is  $\sum_s (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) w_s f_{ijs}$  in which  $\tau$  is a tortuosity factor that accounts for the actual distance that must be traveled due to the available geography and transportation infrastructure. Another cost involved in our models is conversion cost. Unit conversion cost to produce a gallon of biofuel at the biorefinery is specified by  $C^{GC}$ . The total

conversion cost is thus  $\sum_{j,k,s} C^{GC} w_s q_{jks}$ . Biofuel is shipped to the MSA by pipelines at a unit cost of  $C^{GT}$ , so the total biofuel transportation cost equals  $\sum_{j,k,s} D_{jk} C^{GT} w_s q_{jks}$ . To define the cost of the biofuel shortage from mandate, a penalty which equals to the RIN value is considered for every gallon of shortage. Total capital cost to build the biorefineries is  $\sum_{l,j} C_l^B \delta_{lj}$ . We adopt the amortized capital investment concept. Therefore, the annual payments for a period of  $t = 30$  years with interest rate of  $ir = 8\%$  is:

$$\text{PMT}(\text{Investment}) = \text{Investment} \left( \frac{ir(1+ir)^t}{(1+ir)^t - 1} \right)$$

We considered two approaches in the objective function to maximize the total profit. The first is to maximize the expected value of the total profit which is referred to as  $E(\text{Profit})$  in this paper. The model with objective of  $E(\text{Profit})$  is formulated as follows:

$$\begin{aligned} \max \quad & \sum_{j,k,s} P_{ks} w_s q_{jks} + \sum_{j,k,s} X \gamma w_s q_{jks} - \sum_{i,j,s} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) w_s f_{ijs} \\ & - \sum_{j,k,s} (C^{GC} + D_{jk} C^{G,T}) w_s q_{jks} - \text{PMT} \left( \sum_{l,j} C_l^B \delta_{lj} \right) - \sum_{k,s} w_s s h_{ks} \text{RIN} + \sum_{k,s} w_s s p_{ks} \text{RIN} \\ \text{s.t.} \quad & \text{Constraints (3.1) - (3.10),} \\ & f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\ & q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\ & s h_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\ & s p_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\ & \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L. \end{aligned}$$

Using the objective of  $E(\text{Profit})$  does not explicitly address the risks associated with profit. Therefore, in the second approach, we adopt the CVaR of



profit for the objective function. For a distribution of the profit, the definition of VaR and CVaR is considered for the tail on the *left* side of a probability density function.

The  $\text{VaR}_{1-\beta}$  of a random variable of  $X$  is the highest value of  $t$  such that, with probability  $\beta$ , the profit will not be less than  $t$ , whereas the  $\text{CVaR}_{1-\beta}$  is the conditional expectation of profit below that amount  $t$ , as follows

$$\begin{aligned}\text{VaR}_{1-\beta}(X) &= \sup \{t : \Pr(X \geq t) \geq 1 - \beta\}, \\ \text{CVaR}_{1-\beta}(X) &= E[X | X \leq \text{VaR}_{1-\beta}].\end{aligned}$$

For a discrete distribution, another representation of  $\text{CVaR}_{(1-\beta)}$  is

$$\text{CVaR}_{1-\beta}(X) = \sup_t \left\{ t - \frac{1}{\beta} E[(t - X)_+] \right\}. \quad (3.12)$$

The aim of the second approach is to maximize the CVaR of the total profit which is referred to as  $\text{CVaR}(\text{Profit})$  in this paper. The notation related to the new assumptions are included in Table 3.2. Auxiliary variables  $\zeta$  and  $v_s$  are introduced to linearize CVaR of the profit according to (3.12).

Table 3.2 Updated parameters for the stochastic model with objective of  $\text{CVaR}(\text{Profit})$

Profit <sub>s</sub>	Total profit for scenario $s$ ;
Revenues	Revenue for scenario $s$ ;
Cost <sub>s</sub>	Total cost for scenario $s$ ;
$\zeta, v_s$	Variables defined to formulate CVaR of the profit.

The model with the objective of  $\text{CVaR}(\text{Profit})$  associated with  $\beta$ -percentile is presented in the following formulation.

$$\begin{aligned}
\max \quad & \zeta - \frac{1}{\beta} \sum_s w_s v_s \\
s.t. \quad & v_s \geq \zeta - \text{Profit}_s, \quad \forall s \in S, \\
& v_s \geq 0, \quad \forall s \in S, \\
& \text{Profit}_s = \text{Revenue}_s - \text{Cost}_s, \quad \forall s \in S, \\
& \text{Revenue}_s = \sum_{k,j} P_{ks} q_{jks} + \sum_{j,k,s} X \gamma w_s q_{jks} + \sum_{k,s} w_s s p_{ks} \text{RIN}, \quad \forall s \in S, \\
& \text{Cost}_s = \sum_{i,j} (C_{is}^{SC} + \tau D_{ij} C_s^{ST}) f_{ijs} + \sum_{j,k} (C^{GC} + D_{jk} C^{GT}) q_{jks} \\
& \quad + \text{PMT} \left( \sum_{l,j} C_l^B \delta_{lj} \right) + \sum_{k,s} w_s s h_{ks} \text{RIN}, \quad \forall s \in S, \\
& \text{Constraints} \quad (3.1) - (3.10), \\
& f_{ijs} \geq 0, \quad \forall i, j \in N, \quad \forall s \in S, \\
& q_{jks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& s h_{ks} \geq 0, \quad \forall k \in M, \quad \forall s \in S, \\
& \delta_{lj} \in \{0, 1\}, \quad \forall j \in N, \quad \forall l \in L.
\end{aligned}$$

### 3.3 Case Study

In this section a case study is applied for the proposed models to investigate the impact of different policies. The goal of the stochastic mixed integer linear models is to design a biorefinery supply chain with the consideration of uncertainties. The problem is formulated in two mathematical models with two different objective functions:  $E(\text{Profit})$  and  $CVaR(\text{Profit})$ . The models consider the uncertainties in the fuel market price, feedstock supply, and logistic costs, while applying biofuel policies. These models apply the CVaR of shortage as a tool to control the shortage from mandate biofuel in the system.

In biofuel supply chain system in the state of Iowa, biomass can be harvested and collected in every county in the state. Then the feedstock is transported from the counties to the biorefineries for conversion to biofuel. The biofuel is transported to the demand areas or MSAs in Iowa. It is assumed that the transportation distance within the county has a negligible effect on feedstock transportation costs. The model is aimed to determine the optimal biorefineries locations and capacities with the objective of maximizing the annual profit while controlling the risk of the biofuel shortages at the MSAs, as well as considering the policies in the system.

In the rest of this section, we first explain the data used in the case study, and then we analyze and discuss the impacts of the policies on the output.

### 3.3.1 Data Sources for the Case Study

The potential biomass harvesting locations in Iowa are 99 counties in this state. We consider each county as a candidate location to build a biorefinery with capacity level of 1000, 1500 or 2000 ton per day for the conversion to biofuel. The maximum available budget assigned to this project is \$5,000,000,000. There are 21 MSAs in Iowa which are considered as the demand areas. Biofuel mandate at each MSA is estimated as a percent of the state-level gasoline consumption as provided by Energy Information Administration (EIA). This percent is based on the ratio of the population within the MSA and the total population of the state. Figure 3.2 shows the map of the state illustrating the average of available biomass at each county, as well as the levels of gasoline consumption at each MSA.

We assume the confidence levels to define the CVaR of shortage  $\alpha$  and CVaR of profit  $\beta$  are both 20%. The impacts of these confidence levels are important in the result of the decision, however, the study of that is not within the scope of our discussion. We also assume that the upper bound for biofuel shortage at

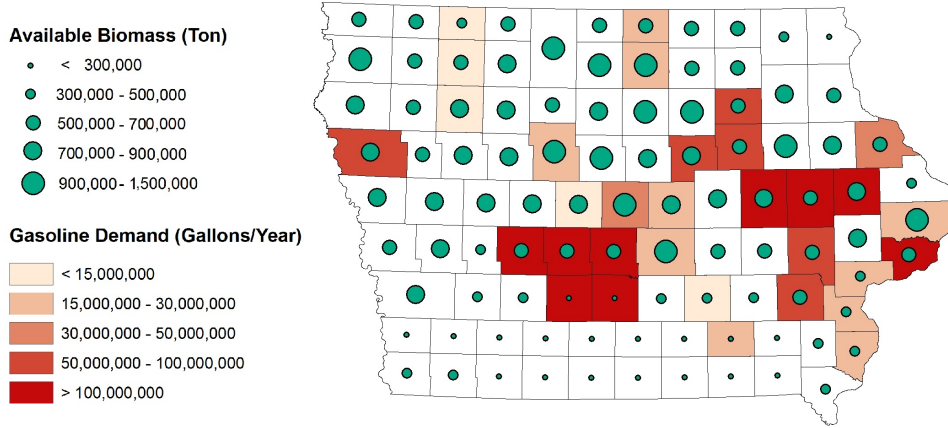


Figure 3.2 Available biomass and gasoline demand in Iowa

MSAs is 800,000,000 gallons per year.

Tortuosity factor  $\tau$  is considered 1.29, which is multiplied by distances and shows the actual distances that must be traveled according to the geographical infrastructure. Material loss factor  $e$ , which accounts for possible losses during loading, transportation, and unloading, is assumed to be 0.05. Based on the experimental data, the biorefinery process yield of feedstock,  $Y$ , is assumed to be 0.218. The sustainability factors,  $S_i$ , to be 0.718 at all counties [44].

We considered 3 cases for the gasoline mandate supposed to be satisfied by biofuel. These scenarios include 10%, 20% and 30% of the total gasoline mandate in each MSA ( $\lambda$ ). We also considered 3 cases for percentages of pass-through ( $\gamma$ ) including 0%, 50% and 100%. In addition, we assume that tax credit for every gallon of biofuel ( $X$ ) is \$1.1, and RIN is \$2.

Scenarios for the problem are considered based on the combination of the uncertain parameters. We generated the scenarios using the average values of the parameters and their deviation according to the historical records. For this problem, we considered 16 scenarios for available feedstock, 3 scenarios for price of gasoline, 2 scenarios for feedstock collection and loading costs, and 2 scenarios for transportation cost. Possible scenarios and their probabilities

generated for each parameter are listed in Tables 3.3-3.6. The combination of these scenarios constructs 192 scenarios in total for this problem.

Table 3.3 Scenarios for available feedstock

Scenario	Available feedstock	Probability
Scenario 1	$A - 8\%A$	1/16
Scenario 2	$A - 7\%A$	1/16
Scenario 3	$A - 6\%A$	1/16
Scenario 4	$A - 5\%A$	1/16
Scenario 5	$A - 4\%A$	1/16
Scenario 6	$A - 3\%A$	1/16
Scenario 7	$A - 2\%A$	1/16
Scenario 8	$A - 1\%A$	1/16
Scenario 9	$A + 1\%A$	1/16
Scenario 10	$A + 2\%A$	1/16
Scenario 11	$A + 3\%A$	1/16
Scenario 12	$A + 4\%A$	1/16
Scenario 13	$A + 5\%A$	1/16
Scenario 14	$A + 6\%A$	1/16
Scenario 15	$A + 7\%A$	1/16
Scenario 16	$A + 8\%A$	1/16

Table 3.4 Scenarios for price of gasoline

Scenario	Price of gasoline	Probability
Scenario 1	$P - 10\%P$	1/3
Scenario 2	$P$	1/3
Scenario 3	$P + 10\%P$	1/3

### 3.3.2 Results Analysis and Discussion

We solve each of the two optimization models proposed in this paper with nine different assumptions on gasoline mandate in each MSA ( $\lambda$ ) and percentages of pass-through ( $\gamma$ ). These assumptions are the combination of three cases for ( $\lambda$ ) and three cases for ( $\gamma$ ). We consider three cases for the gasoline mandate supposed to be satisfied by biofuel including 10%, 20% and 30% of the total

Table 3.5 Scenarios for feedstock collection and loading cost

Scenario	Feedstock collection and loading cost	Probability
Scenario 1	$C^{SC} - 10\%C^{SC}$	1/2
Scenario 2	$C^{SC} + 10\%C^{SC}$	1/2

Table 3.6 Scenarios for transportation cost

Scenario	Transportation cost	Probability
Scenario 1	$C^{ST} - 10\%C^{ST}$	1/2
Scenario 2	$C^{ST} + 10\%C^{ST}$	1/2

gasoline mandate in each MSA ( $\lambda$ ). We also consider 3 cases for percentages of pass-through ( $\gamma$ ) including 0%, 50% and 100%. The results of the model for the combination of these cases are shown in Table 3.7.

Table 3.7 provides the results of the model with the objective of expected value of the profit. As we can see, it is obvious that as the percentage of the mandate increases, the total profit decreases, because there are more strict mandate should be satisfied in the system. It shows the necessity of more encouraging policies when the mandate percentage is larger. In addition, as the percentage of pass-through goes up, the total profit increases in all cases.

By increasing the mandate, there will be more shortage for mandate, so shortage cost will increase. On the other hand, the profit from credit gained by surplus of biofuel production will increase significantly when the percentage of mandate increases from 10% to 20% when the percentage of pass-through is 0% or 50%. But when the percentage of pass-through is 100%, the profit from credit gained by surplus of biofuel production decrease from 10% to 20%. In all values of  $\gamma$ , when the percentage of pass-through is 100%, the credit gained by surplus of biofuel production is larger compared to other percentages of pass-through. In cases with  $\lambda$  of 10% and 20%, it is noticeable that when the pass-through increased from 50% to 100%, not all the revenue from pass-through

Table 3.7 Results of the model with the objective of expected value of the profit

	$\gamma$	$\lambda$		
		10%	20%	30%
Total profit	0%	453 M	329 M	134 M
Revenue of selling biofuel		4,547 M	4,422 M	4,232 M
Revenue of Pass-through		0	0	0
Conversion and gas transportation Cost		3,028 M	3,022 M	3,019 M
Biomass collection and transportation Cost		643 M	643 M	637 M
Investment cost		423 M	423 M	429 M
Shortage cost		7 M	32 M	33 M
Credit		7 M	26 M	20 M
Total profit	50%	455 M	331 M	136 M
Revenue of selling biofuel		4,547 M	4,422 M	4,232 M
Revenue of Pass-through		2 M	2 M	2 M
Conversion and gas transportation Cost		3,028 M	3,022 M	3,019 M
Biomass collection and transportation Cost		643 M	643 M	637 M
Investment cost		423 M	423 M	429 M
Shortage cost		7 M	33 M	33 M
Credit		7 M	26 M	20 M
Total profit	100%	456 M	332 M	138 M
Revenue of selling biofuel		4,547 M	4,422 M	4,232 M
Revenue of Pass-through		4 M	4 M	4 M
Conversion and gas transportation Cost		3,028 M	3,022 M	3,019 M
Biomass collection and transportation Cost		643 M	643 M	637 M
Investment cost		423 M	423 M	429 M
Shortage cost		7 M	11 M	33 M
Credit		7 M	4 M	20 M

is reflected on the profit. The revenue from the pass-through is increased by 2M and the profit is only increased by 1M. In addition, when the percentage of mandate increased, there is a remarkable increasing in the credit from selling RINs, however, the shortage costs increase as well.

Table 3.8 summarizes the results of the model with the objective of CVaR of the profit. In general, the total profit from this model is less than the total profit from the model with the objective of expected value. It is obviously because of the fact that the CVaR is more conservative rather than expected Value. In this model, the revenue from selling biofuel and pass-through is less than the first model. The other observation is the difference of credit and shortage cost in these two models. When the percentage of mandate is 10%, the credit from

Table 3.8 Results of the model with the objective of CVaR of the profit

	$\gamma$	$\lambda$		
		10%	20%	30%
Total profit	0%	260 M	168 M	73 M
Revenue of selling biofuel		2,235 M	2,438 M	3,328 M
Revenue of Pass-through		0	0	0
Conversion and gas transportation Cost		1,486 M	1,701 M	2,422 M
Biomass collection and transportation Cost		273 M	318 M	469 M
Investment cost		212 M	242 M	350 M
Shortage cost		33 M	34 M	34 M
Credit		30 M	25 M	20 M
Total profit	50%	261 M	169 M	74 M
Revenue of selling biofuel		2,235 M	2,438 M	3,328 M
Revenue of Pass-through		1 M	1 M	1 M
Conversion and gas transportation Cost		1,486 M	1,701 M	2,422 M
Biomass collection and transportation Cost		273 M	318 M	469 M
Investment cost		212 M	242 M	350 M
Shortage cost		33 M	34 M	34 M
Credit		30 M	25 M	20 M
Total profit	100%	262 M	176 M	76 M
Revenue of selling biofuel		2235 M	2493 M	3328 M
Revenue of Pass-through		2 M	2 M	3 M
Conversion and gas transportation Cost		1486 M	1737 M	2422 M
Biomass collection and transportation Cost		273 M	327 M	469 M
Investment cost		212 M	246 M	350 M
Shortage cost		33 M	34 M	34 M
Credit		30 M	25 M	20 M

selling RINs and also shortage cost are remarkably increasing compared to the previous model.

Generally, in both models, as the percentage of pass-through increases, the total profit increases slightly, but as the percentage of mandate increases, the total profit decreases considerably.

### 3.4 Conclusion

To reduce the dependence on fossil fuels and to address climate change concerns, U.S. policymakers have employed a variety of policies to support the production and consumption of biofuels. Biofuel industry has been highly affected by these policies. This study has attempted to analyze the impacts



of RFS mandates and pass-through on the biofuel supply chain models under uncertain sources of feedstock availability and logistic costs. In order to achieve this goal, we studied the models formulated with two different approaches in the objective functions. First approach is maximizing expected value of profit and the second approach is maximizing the CVaR of the profit. We also applied CVaR in the constraints of the models to control the shortage from mandates.

The assessment undertaken in this study shows that considerable increase in pass-through has a slight increase in the total profit. The increase in the mandate of biofuel has a remarkable impact on decreasing the total profit. The comparison between two models with different objective functions shows that the revenue from pass-through in the model with the objective of expected value is more than the revenue from pass-through in the model with the objective of CVaR. However, the credit from RINs in the model with the objective of expected value is less than the same credit in the model with the objective of CVaR. In general, regardless of the policies, the total profit decreased considerably in the model with the objective of CVaR of the profit.

## CHAPTER 4. GENERAL CONCLUSION

### 4.1 Conclusion

Biofuels play an important role in providing clean and secure energy and promoting the economic growth. One of the most important and challenging issues for biofuel production is the biofuel supply chain network design. The general structure of the biofuel supply chain consists of biomass production, harvesting, transportation, conversion and fuel distribution. The biomass is harvested at the farms and shipped to the biorefineries. At the biorefineries, the feedstock is converted to biofuel and then transported to the demand areas. In biofuel supply chain network design, one of the biggest challenges is to deal with uncertainties along the supply chain.

The motivation in this study is to design the biofuel supply chain network under uncertainty and also explore the impacts of the different policies on the supply chain network. We proposed a mathematical programming framework with the approach of two-stage stochastic programming to determine the capital investment decisions on the locations and capacities of the biorefineries, the feedstock transportation and biofuel delivery decisions. Before the uncertainties are realized, the first-stage decisions have to be made, and the second-stage decisions are made after the realization of the system parameters. The first-stage decisions include the capital investment decisions (the locations and capacities of the biorefineries). Once the uncertainties are realized, the second-stage decisions are made which include the flows of the biomass from the harvesting sites to biorefineries and the flows of the biofuel to the demand areas.

The uncertainties considered in this problem consist of feedstock supply, fuel market price, and logistic costs. Two modeling approaches are adopted in the objective function formulation: expected value and CVaR of profit. In the first approach, the objective function is to maximize the expected value of profit. The profit of the project is an important performance measure to evaluate the effectiveness of the decision. However, the expected profit approach does not explicitly address the risk of decision making under the unfavorable events. In order to manage the system risks, we adopted CVaR of profit as the second approach in the objective function.

It should be noted that it is of great importance to control the shortage of demand in the system. One of the challenges in this model is incurring a large amount of shortage in a single demand MSA. We design a risk measure in the constraints to level the shortage and decrease the probability of larger shortage occurring in the network. We consider CVaR of the shortage and set an upper bound on that to control the risk of shortage through demand areas.

In the case study, the state of Iowa is selected due to the data availability to demonstrate the effectiveness and applicability of the proposed modeling framework. There are 99 counties in Iowa with biomass feedstock supply, each of which is considered as a candidate location for biorefinery. The demand zones are 21 MSAs located in the state. We implemented the proposed models with different assumptions in the case study to compare and analyze the results: the model with objective function of  $E(Profit)$  with and without the CVaR constraints on the shortage, and also the model with objective function of  $CVaR(Profit)$  with and without the CVaR constraints on the shortage.

Comparisons between models with two different objective functions indicates that unsurprisingly the models with objective function of  $E(Profit)$  provide smaller shortages, whereas the models with objective function of  $CVaR(Profit)$  yield larger shortages. In addition, models without the CVaR constraints on

the shortage result in a larger concentrated amount of shortages in the MSAs which is due to that there is no upper bound on the amount of shortage in a specific demand area. However, the models with CVaR constraints on the shortage, result in more MSAs with shortages, but the amount of shortage in each MSA is reduced. In other words, enforcing an upper bound on the CVaR of the shortage prevent the occurrence of a large amount of shortage in a single MSA. This result is as expected, as the CVaR constraints set a limit on the amount of shortage in a single MSA.

Biofuel policies and mandates legislated by the government have significant impacts on the biofuel industry. We attempt to study the impacts of policies such as RFS and tax credit on the biofuel supply chain models under uncertain sources. To achieve this goal, the two-stage stochastic modeling framework with two approaches in the objective functions were employed. In addition, CVaR is applied in the constraints of the models to control the shortage from mandates. These models are applied for the case study in Iowa. The comparison between two models with different objective functions shows that as the revenue from pass-through in the model with the objective of expected value is more than the revenue from pass-through in the model with the objective of CVaR. However, the credit form RINS in the model with the objective of expected value is less than the same credit in the model with the objective of CVaR. In general, regardless of the policies, the total profit decreased considerably in the model with the objective of CVaR of the profit.

In summary, this study aims to provide a mathematical modeling framework for the biofuel supply chain network design under uncertainty. Two types of objective functions have been considered: expected value of profit and CVaR of profit. The first approach focuses on maximize the expected profit where the latter approach is more on the mitigation of system risk under averse conditions. The impacts of incorporating the stochastic shortage control are also investi-

gated by incorporating the CVaR of shortage as a constraint in the model. Moreover, we explored the impacts of biofuel policies and mandates on the proposed supply chain models.

## 4.2 Future Study

Biofuel supply chain network design depends on many parameters and factors. However, the proposed method only provides a basic framework to study the biofuel supply chain under uncertainty. It is suggested to extend these models to consider additional operational assumptions in future studies. In addition, the larger the number of scenarios, the more accurate the decisions would be. Consequently, the computational complexity would substantially increase. Therefore, exploring more efficient algorithms to solve the problem could be another direction for future work in this area.

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